The Dutch business cycle: a finite sample approximation of selected leading indicators.*

Ard H.J. den Reijer†

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Abstract

In this study we construct a business cycle indicator for the Netherlands. The Christiano-Fitzgerald band-pass filter is employed to isolate the cycle using the definition of business cycle frequencies as waves with lengths longer than 3 years and shorter than 11 years.

The coincident business cycle index is based on industrial production, household consumption and staffing employment. These three variables represent key macroeconomic developments, which are also analysed by both the CEPR and NBER dating committees. The composite leading index consists of eleven indicators representing different sectors in the economy: three financial series, four business and consumer surveys and four real activity variables, of which two supply- and two demand-related.

The pseudo real-time performance of the composite indicator is analyzed by the extent to which the indicator gets revised as more data becomes available. Finally, the composite leading indicator is employed in a bivariate Vector Autoregressive model to forecast GDP growth rates.

Keywords: band-pass filter, turning points, forecasting GDP.

JEL Code: C82, E32, E37

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†ard.den.reijer@riksbank.se, Monetary Policy Department, Sveriges Riksbank, SE-10337 Stockholm, Sweden, tel: +46 8 787 0149

1 Introduction

Various commercial, academic and government institutions use a business cycle indicator as an instrument to measure and predict business cycle developments and turning points. An accurate assessment of the current and future state of the business cycle is valuable information in the decision process of policy makers and businesses. Most institutions who regularly publish business cycle indicators, follow the approach of using leading and coincident indicators that is developed at the National Bureau of Economic Research (NBER) in the US in the 1930s. Within this dominant methodology, the indicators of the various institutions differ in the specific choices regarding variable selection, the identification of the cyclical patterns, determining the leading/lagging properties of the variables and the weighing of the variables into a single index. Handbooks as user guides for the construction of leading indicators are published by The Conference Board (TCB, McGuckin, 2001), the Economic Cycle Research Institute (ECRI, Achuthan en Banerji, 2004) and the Organisation for Economic Co-operation and Development (OECD, Nardo *et al.*, 2008). The institutions construct uniform business cycle indicators for 9 countries and the euro area, 18 countries and 7 zone aggregates and 35 countries and 10 zone aggregates respectively.

The OECD also runs an indicator for the Netherlands, as do the Netherlands Bureau for Economic Policy Analysis (CPB, Kranendonk *et al.*, 2005), Rabobank (Wolters, 2006), Statistics Netherlands (CBS, Van Ruth en Schouten, 2004), the Centre for Economic Research at the University of Groningen (CCSO, Jacobs, 1998) and the Dutch central bank (DNB, Berk en Bikker, 1995). All these indicators aim at describing and forecasting[1] the Dutch business cycle, but differ in applied methodologies and empirical applications. We document the operational Dutch indicators and confront them with a band-pass filtered cycle that is required to be timely available and more broadly based than solely on manufacturing production.

In section 2, we explore the concept of the business cycle and discuss the method of band-pass filtering to separate the trend and cyclical motions of a variable. In section 3, we construct a composite reference index, which is based on timely available coincident macroeconomic variables that are closely monitored by business cycle dating committees. In a similar way we construct a composite leading indicator, which is based on cyclically leading financial, survey and real activity variables. In section 4, we analyze the extent to which the composite indicators get revised as more data observations become available. Finally, the last section shows how the composite leading indicator can be employed to generate forecasts for GDP growth rates.

2 The business cycle

Business cycles can broadly be defined as oscillating motions of economic activity. Consecutive cycles are separated by turning points, that is peaks and troughs. The *classical* cycle considers the fluctuations of the level of economic activity, see Harding en Pagan (2002), while the *deviation* cycle considers the

[1] An exception is Statistics Netherlands (CBS), whose indicator only aims at describing the Dutch business cycle.

fluctuations around some trend[2]. The recession of the classical cycle is characterized by an absolute decline in the level of economic activity, that is by negative growth rates. The recession of the deviation cycle is characterized by economic growth rates that are below potential growth. Classical recession phases are always a subsample of the recession phases of deviation cycles[3]. Deviation cycles gained popularity, because periods of negative growth rates have been exceptional in industrialized countries since the Second World War. So, deviation cycles could more naturally be related to the fluctuations observed in the level of employment and unemployment. Moreover, the concept of a deviation cycle as the output gap between actual output and potential output gained policy relevance through the stronger focus on Taylor-rule driven monetary policy and cyclically adjusted government balances.

In this study, we adopt the definition of a business cycle as all the intrinsic cyclical motion visible in macroeconomic data consisting of waves within a specified frequency interval. This interval of business cycle frequencies corresponds with Burns en Mitchell's (1946) taxonomy of business cycles as waves lasting longer than a pre-specified minimum duration and shorter than a maximum duration. The business cycle frequencies can be isolated by an ideal band-pass filter, which is then used as a benchmark for finite sample approximations. Band-pass filters are designed to adequately extract a specified range of periodicities without altering the properties of this extracted component. The assumption of an ideal band-pass filter is implicit in the work of Baxter en King (1999) (BK-filter), Christiano en Fitzgerald (2003) (CF-filter), Pedersen (2001) and to a certain extent Pollock (2000).

In order to isolate the cyclical component ψ_t out of the time series x_t with the period of oscillation between p_l and p_u, where $2 \leq p_l < p_u < \infty$ using a linear filter $\psi_t = B(L)x_t$, where $B(L) = \sum_{j=-\infty}^{\infty} B_j L^j$ and the lag operator L such that $L^j x_t = x_{t-j}$, the weights B_j of the ideal band-pass filter are defined as (see e.g. Priestley, 1982, page 275):

$$\begin{cases} B_j = \frac{\sin(j\omega_l)-\sin(j\omega_u)}{j\pi}, j \neq 0 \\ B_0 = \frac{b-a}{\pi}, \omega_u = \frac{2\pi}{p_u}, \omega_l = \frac{2\pi}{p_l} \end{cases} \tag{1}$$

Given the finite amount of T observations $\{x_t\}_{t=1}^{T}$, then $\widehat{\psi}_t$ is a linear projection of ψ_t onto every element in the sample set, x_t, such that there is a different projection problem for each date t. The filter weights can be determined by a

[2] A third approach to business cycle representation is the so-called growth-rate cycle. Calculating growth rates can however also be interpreted as a detrending device, see for a discussion Harding en Pagan (2005). Calculating growth rates is equivalent to applying the first difference filter, which induces an artificial phase shift $\theta(p) = \tan^{-1}\left[\frac{\sin\left(\frac{2\pi}{p}\right)}{1-\cos\left(\frac{2\pi}{p}\right)}\right] > 0$ with p the duration of the cycle. (see page 275 Hamilton, 1994).

[3] Assume that a business cycle variable y_t admits the log-additive decomposition, $y_t = \tau_t + \psi_t$, for which τ_t is the trend and ψ_t the deviation cycle. Then the growth rate can be decomposed into trend growth and cyclical change: $\Delta y_t = \Delta\tau_t + \Delta\psi_t$. The recession phase of a deviation cycle $\Delta\psi_t < 0$ implies a lower than trend (or potential) growth rate: $\Delta y_t < \Delta\tau_t$. A classical recession phase, that is $\Delta y_t < 0$ implies a deviation cycle recession (reasonably assuming a non-negative trend growht rate: $\Delta\tau_t \geq 0$).

least squares minimization criterion:

$$\min_{\widehat{B}_j} E\left[\left(\left(B(L)-\widehat{B}(L)\right)x_t\right)^2\right], \forall t = 1...T \tag{2}$$

The quadratic minimization problem (2) depends on the observations $\{x_t\}$ and Schleicher (2004) derives closed-form solutions[4] in case x_t follows an arima (p, d, q)-process for $d = 0, 1$. The optimal approximate filter coefficients are the ideal band-pass filter coefficients weighted by the auto-correlation properties of the time series, which then need to be estimated first. As corollaries under additional restrictions, Schleicher (2004) shows that the approximations of Baxter en King (1999) and Christiano en Fitzgerald (2003) are special cases in which the underlying data generating process is white noise, i.e. arima(0,0,0), respectively a random walk, i.e. arima(0,1,0). The BK-filter coefficients look like $\widehat{B}_j^{BK} = B_j + \frac{\Delta}{(1+2k)}, j = 0, \pm 1, ..., k$, with $\Delta = -\left[B_0 + 2\sum_{j=1}^{k} B_j\right]$. Note that BK-filter is a time invariant symmetric filter, i.e. $\widehat{B}_j^{BK} = \widehat{B}_{-j}^{BK}$ $\forall t$ and does not induce an artificial phase shift[5].

The CF-filter coefficients look like:

$$\begin{cases} \widehat{B}_j^{p,f} = B_j, j = -p+1, ..., f-1 \\ \widehat{B}_{-p}^{p,f} = \frac{B_0}{2} - \sum_0^{p-1} B_j, \widehat{B}_f^{p,f} = \frac{B_0}{2} - \sum_0^{f-1} B_j \end{cases} \tag{3}$$

Christiano en Fitzgerald (2003) question the restrictions of symmetry, i.e. $p = f$, so effectively allowing for filter induced phase shifts, and constancy, i.e. $p = f = k$ in order to always use of the full sample of available observations. Moreover, they state that the underlying Random Walk assumption for x_t in the optimization (2) represents Granger's (1966) typical spectral shape of a trending macroeconomic variable sufficiently well in practice. The resulting weights of the CF-approximation $\widehat{B}_j^{p,f}$ are sample size dependent (as $T = p+f+1$), which effectively transmits to the filtered series. However, an important feature of approximate band-pass filters is that $\widehat{\psi}_t \to \psi_t$ as both $\widehat{B}_j^{BK}$ and $\widehat{B}_j^{p,f}$ converge to their (identical) infinite sample equivalents B_j as the window size increases due to additional observations, i.e. $k \to \infty$ and $p, f \to \infty$ respectively and $B_j \to 0$ for distant observations $j \to \infty$.

Canova (1999) examines the sensitivity of turning point classification to applying different trend-cycle decomposition procedures to GDP using as a benchmark the official turning point chronology of the NBER's business cycle dating committee. Of all the employed trend estimators, two filters, namely Hodrick en Prescott's (1997) filter (HP-filter) and the bandpass filter prove to be superior in detecting the NBER's turning points in terms of the number of missed turning points and false alarms. Based on a qualitative comparison, Zarnowitz

[4]Wildi's (2008) Direct Filter Approach is another finite sample approximation that extensively elaborates on spectral methods with a focus on the end of the sample.

[5]For the filtered sequence $\widehat{\psi}_t = \widehat{B}(L)x_t$, the filter induced phase-shift is determined by the cross-covariance function, or cross-spectrum (see Priestley, 1982) $f_{\psi\widehat{\psi}}$, between ψ_t and $\widehat{\psi}_t$. This is given by:
$f_{\psi\widehat{\psi}}(\omega) = \widehat{B}^{p,f}\left(e^{-i\omega}\right) B\left(e^{-i\omega}\right) f_x(\omega)$.
The phase is related to the complex part of $f_{\psi\widehat{\psi}}(\omega)$. This equals zero, given that both $B\left(e^{-i\omega}\right)$ and $f_x(\omega)$ are real, if and only if $\widehat{B}\left(e^{-i\omega}\right) = \widehat{B}\left(e^{i\omega}\right)$, i.e., that $\widehat{B}_j = \widehat{B}_{-j}$.

en Ozyildirim (2006) conclude that the HP- and BK-filters provide comparable in-sample results to the NBER´s Phase Average Trend (PAT, see Boschan en Ebanks, 1978) procedure, which is a data driven piece-wise linear trendfilter. Kranendonk *et al.*'s (2005) empirical analysis of Dutch data shows that the in-sample statistical criteria of the CF-filter are comparable to those of the BK- and HP-filter, but that the CF-filter shows the lowest sensitivity to new data. The tail behavior of the filter refers to the extent to which estimates get revised over time as more data becomes available. In an empirical analysis of cycle extraction methods, Van Ruth en Schouten (2004) conclude in terms of tail behavior and real-time turning point detection that both the CF-filter and the HP-filter are subject to relatively sizeable revisions.

3 Measuring the business cycle

Using the CF-filter to isolate business cycle frequencies requires an *a priori* specification of the minimum and maximum duration of a business cycle. Burns en Mitchell's (1946) taxonomy of business cycle frequencies is that *in duration business cycles vary from more than one year to ten or twelve years.* For U.S. data, Stock en Watson (2000) and Baxter en King (1999) use the convention of a business cycle as the cyclicality of GDP with a duration between 6 and 32 quarters. This convention is based on the NBER chronology of business cycle turning points, which shows that the shortest business cycle since 1858 lasted 6 quarters and the longest cycles are almost all shorter than 8 years. For the business cycle of the euro area, Agresti en Mojon (2001) employ an upper bound on the duration of 10 years. The euro area experienced 3 periods of recession during the last 30 years. Van Ruth en Schouten (2004) perform an empirical analysis on Dutch GDP using different cycle extraction methods and find that the average duration of the cycle is robust and lies between 10 and 11 years. The average length of the downswing from peak-to-trough is 3 years. A similar analysis for industrial production results in an average cyclical duration of just below 9 years and a peak-to-trough downswing of 2.5 years. These averages for industrial production are corrected for minor cycles. Based on this analysis, we use the CF-filter with a lower bound on the duration of 3 years and an upper bound of 11 years. The minimum duration requirement of 3 years aims to filter out the minor cycles in addition to the seasonal ones such that the resulting business cycle matches more closely its benchmark of cyclical GDP.

3.1 The composite reference index

While real GDP as the aggregate of all economic activity constitutes an important statistic for business cycle measurement, business cycle dating committees monitor several macroeconomic variables as the cyclical fluctuations of GDP don't always move synchronously to the ones of its underlying components, which can even move anti-cyclically. The Centre for Economic Policy Research´s (CEPR) business cycle dating committee defines a recession as the significant decline in the level of economic activity, spread across the economy of the euro area and mostly visible in two or more consecutive quarters of negative growth of GDP, employment and other measures of economic activity. In establishing the chronology, the committee relies on the turning points of GDP, industrial

Table 1: The coincident business cycle indicators that constitute the reference index

Variable	available since	Public. delay (in weeks)	Cross correl. (with GDP)
Industrial production	1965	6	0.9
Household consumption	1995 (1977)	7/8	0.9
Staffing employment	1967	1	0.6

production, employment, consumption and investment in both the aggregate euro area and in the three largest countries. The American NBER´s business cycle dating committee relies on the analysis of GDP, real income, employment, industrial production and the wholesale and retail trade.

It is in general infeasible to identify one single variable, which covers a broad range of economic activity, represents the current stage of the business cycle and is available on a monthly frequency. In addition, other important criteria for selecting the variables for the composite reference index are a limited publication delay and minor data revisions. This means that new data releases are published shortly after the period has ended and that the initially published values are subject to only minor revisions during subsequent publications regarding the same period. The coincident reference index will therefore be composed as a composite index of several synchronous indicators. A composite index as a cross section of the cyclical motions of several variables constitutes a more robust standard of business cycle measurement since the idiosyncrasies of the individual indicators are averaged out.

These considerations lead us to include industrial production, household consumption and staffing employment in the composite reference index of the Dutch business cycle, see Table 1. The volume index of consumption by households is closely related to retail sales, since it consists only of those expenditures for which households pay themselves. The household consumption is only available from 1995 onwards and the appendix shows how it is extended until 1977 using the private consumption of the National Accounts. Industrial production constitutes approximately 25% of GDP and its share is declining relative to the share of services production. Despite this small share, the OECD indices are solely based on industrial production as its cyclical motion is considered a representative statistic for the business cycles.

Employment is a macroeconomic aggregate, which covers the whole range of economic activity. Both Dutch employment and staffing employment are released with a substantial publication delay, but the appendix shows how to create a time series for the staffing employment with a long history based on representative data from the market leader Randstad Netherlands and a timely available update based on representative data from the sector organisation[6]. Total employment for the Netherlands consists for 5% of staffing employment[7]. This market segment is most sensitive to business cycle motions, because companies can every moment adjust their use of staffing services immediately to changing market conditions. For instance, De Groot en Franses (2005) use Randstad-data as a coincident indicator in an error correction specification to forecast the growth rate of GDP.

The cyclical motions of the three variables from Table 1 are graphed in Figure 1. The composite coincident reference index is the unweighted average of the three standardised cyclical motions and is represented in the upper part of Figure 1. The cross-correlation of the composite coincident reference index and the cyclical motion of GDP is 0.9 and is (slightly) higher than the cross-correlations of the three single indicators as shown in Table 1. The composite index as a cross section of the three variables constitutes therefore a more robust measure of economic activity since the idiosyncrasies of the individual indicators are averaged out.

4 The leading business cycle indicator

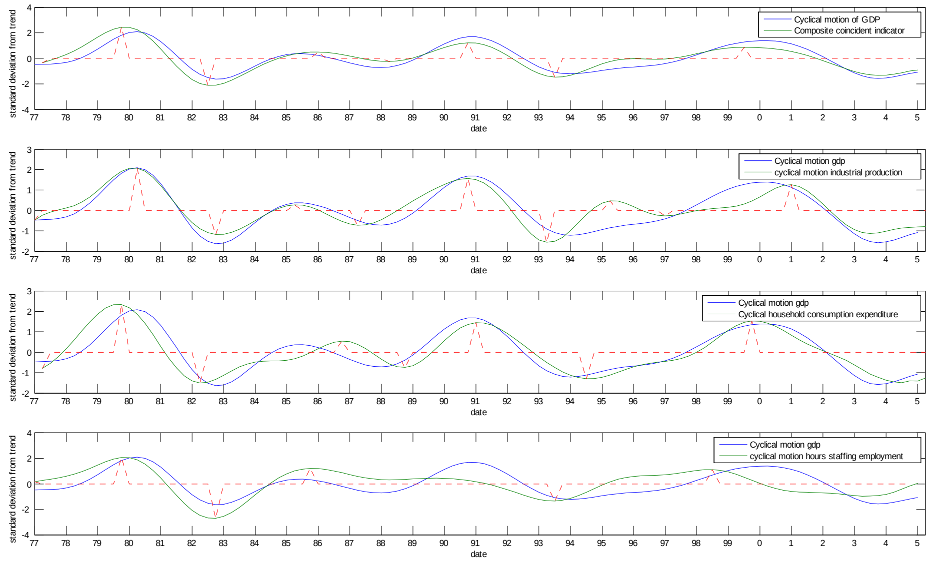
Theory and practice show that recessions originate from different sources and possess different characteristics. Stock en Watson's (2003) overview of the empirical literature on the usefulness of financial indicators for inflation and GDP-growth forecasting concludes that some asset prices possess significant forecasting power for some countries during some time periods, but that it is impossible to identify one single indicator showing a consistently good forecasting performance for all countries during all time periods. A combination of leading indicators in a composite leading index is therefore useful to pick up signals originating from different sectors in the economy.

Nardo *et al.* (2008) and Moore en Shiskin (1967) specify economic and statistical criteria for the selection of leading indicators. Economic reasoning guides the selection of the variables. The selected leading indicators should make up a balanced representation and cover the relevant sectors of the economy. The composition should ideally be well balanced between business and consumer survey results, financial series and real activity variables measuring economic behavior. Economic plausibility requires that the leading indicators should be supported by economic theory either as possible causes of business cycles or as quickly reacting to positive or negative shocks. The leading indicator should show consistent timing by systematically anticipating peaks and troughs with a rather constant lead time. Moreover, the conformity to the general cycle requires the leading indicator to possess good overall forecasting performance, not

[6]see http://www.abu.nl, which is the Dutch association of temporary work agencies and represents more than 60% of the market.

[7]Note that the output produced by a staffing employee employed at an industrial or agricultural company is booked as services production in the National Accounts.

Figure 1: Cyclical motion of GDP and respectively the reference index, industrial production, household consumption and staffing employment



only at peaks and troughs. The statistics criteria require the leading indicators to be promptly available without publication delay and be subject to only minor data revisions. The statistics criteria partly explain the increasing use of surveys and financial variables as leading indicators. Both categories of variables are not subject to data revisions and financial data are directly observable.

The leading indicators are selected based on the above-mentioned criteria. The most important selection criterion for the leading indicators is the conformity with the business cycle as represented by the composite reference index. This criterion is quantified by the cross correlation ρ of the coincident indicator, CI_t, with the cyclical motion of the suitably transformed leading indicator variable, LI_t. The transformation consists of taking the log-specification of the variables, if feasible[8], and *a priori* classifying the variable as pro- or counter-cyclical. The maximum cross-correlation and the corresponding lead time l are then determined by shifting the leading indicator variable over time: $\rho^{\max} = \max_{l=0,\dots,36} \rho\,(CI_t, LI_{t-l})$.

[8]No logarithm is taken in case the variable is scaled as a quotient (for instance interest rates, unemployment rate) or in case the variable can admit negative values or the value zero (for instance trade balance, stock finished products).

Table 2: Statistical criteria of potential leading indicators

Description	log	Maximum Correlation*	Lead* (months)	Covered by
IFO future expectations		0.8065	9	
3 months interest rate		0.8728	26	
yieldcurve		0.7205	30	
order arrivals		0.7751	15	
expected business activity		0.8640	9	
stock finished products		0.7129	10	
Consumer confidence		0.8607	11	
Stock exchange index (AEX)	log	0.7283	7	
House Price real	log	0.7669	7	
Registered motor vehicles	log	0.8104	9	
OECD leading indicator country United States, trend restored	log	0.7728	18	
10 years interest rate		0.7195	21	yield - curve
M3	log	0.3190	5	
M3-real	log	0.1811	3	
M1	log	0.3901	3	
M1-real	log	0.6101	3	
M1-real growht rate		0.5360	23	
Level order position	log	0.4981	3	
Producer Confidence		0.7313	10	expected business activity
Consumer Survey Economic Climate		0.8804	12	consumer confidence
Willingness-to-buy		0.8204	3	
Bankruptcies	-log	0.9410	4	
Hwwa-commodity prices index	-log	0.4638	24	
Contractual wages (CAO)	-log	0.4687	3	
House Price	log	0.7023	8	real house price
Consumer price index	-log	0.6287	3	
Oil Price	-log	0.4294	30	
Capital account balance		0.5375	6	
Credit supply	log	0.4095	10	
Wages Industry, total	-log	0.5524	24	
Trade balance		0.5399	22	
Investement, businesses	log	0.9272	3	
Savings	-log	0.3231	3	
Exports	log	0.6842	3	
Imports	log	0.9164	3	
Unemployment rate		0.5641	3	
Wages, hourly	-log	0.5214	3	
Industrial Production, Belgium	log	0.6457	3	
Industrial Production, Germany	log	0.6880	3	
Industrial Production, U.S.	log	0.8274	6	OECD leading indicator
exchange rate	-log	0.0608	3	
Producer Prices, domestic	-log	0.5408	7	
Producer Prices, foreign	log	0.1088	3	

Notes:

Statistics are derived with respect to the composite coincident index.

Table 3: Turning point dating of GDP, the composite coincident index and leading indicators

	GDP	coincident index	leading indicator	ifo future expectations	Three months interest rate	Term structure	order arrivals	Consumer confidence	expected business activity	Aex	Real house price	New car registration	stock finished products	OECD indicator U.S.
peak	80q2	79m12	80m7	80m3	80m6	78m10	80m7	79m6	80m3		79m4	79m11	80m6	79m1
trough	82q4	82m10	82m12	82m8	83m2	82m11	82m10	84m5	82m9	82m11	83m1	82m5	82m12	83m9
peak	85q3	85m10	85m11	85m12	85m12	86m4	85m7	86m11	85m7	86m7	88m6	87m7	85m4	85m10
trough	88q1	87m12	88m3	87m12	87m12	88m8	88m2	88m10	88m2	88m12		89m8	87m6	87m5
peak	90q4	90m11	90m7	91m6	90m1	90m7	90m3	90m8	91m1	90m12		91m10	89m10	89m9
[trough]						92m4				92m10	92m7			
[peak]						93m4					94m8			
trough	94q1	93m7	94m2	93m10	93m12	95m3	94m2	93m8	93m9		95m12	94m5	93m8	93m2
[peak]		95m10	96m5	95m10			96m4		95m12	94m5	97m4		95m10	95m4
[trough]		96m12		97m3						96m5			97m7	96m12
[peak]				98m10	98m1	98m5							98m11	
[trough]			00m9	00m6			98m3		00m3		99m1		00m3	
peak	00q2	00m9	01m12	01m7			01m8	01m8	01m10	01m4	01m5	00m4	01m10	01m3
trough	03q4	03m10	03m10	03m6	03m6	03m11	03m7	04m1	03m10	03m11	04m6	03m5	03m10	03m12
false signals		2(wrt GDP)	1	2	1	3	1		1	1	3	0	2	0
missed turning points			1		3	3	1	2	1	2	3	2		0
lead time (months)			7	9	26	30	15	11	9	7	7	9	10	18

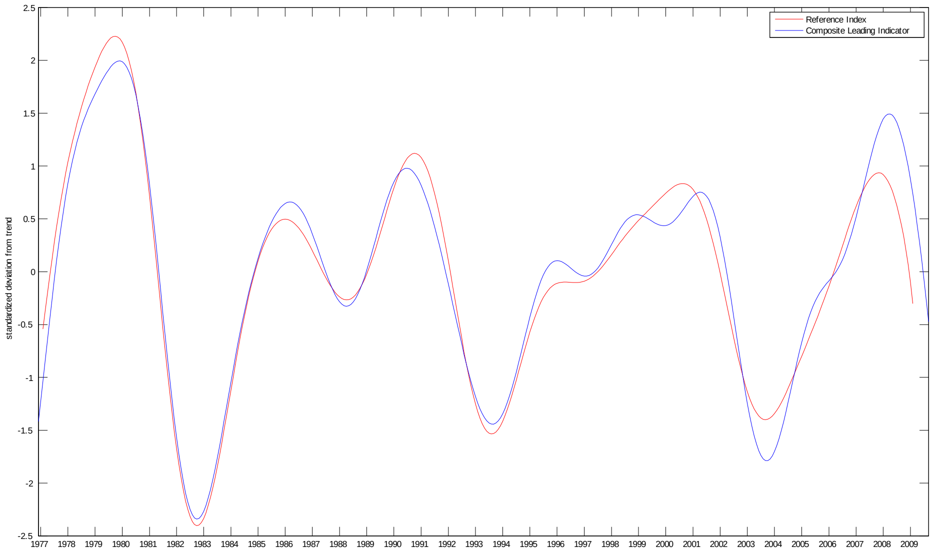
Table 2 shows the resulting optimal values for the collection of potential leading indicator variables (cf Berk en Bikker, 1995) fulfilling the requirements of timely availability and minor revisions. The lead times are determined for the cyclical parts of the potential leading indicator variables defined as cyclical motions with a duration longer than 3 and shorter than 11 years.

Another criterion is that the turning points of the leading indicators manifest themselves with a more or less constant lead time with respect to the turning points of the composite reference index. Bry en Boschan (1971) formulate a procedure to detect the turning points of the business cycle. Essentially, the procedure determines a local extremum conditional on a minimum duration of the cycle and the requirement that peaks and troughs alternate. Harding en Pagan (2002) mathematically formalise this algorithm and analyse the resulting business cycles without reference to an explicitly specified trend development. This study adopts a dating algorithm for deviation cycles that determines local extrema conditional on alternating peaks and troughs and that a peak (trough) of the deviation cycle is positive (negative). So, a peak turning point exist at time t if $(1-L)\,LI_{t-1} > 0$ and $(1-L)\,LI_t < 0$ conditional on $LI_t > 0$ and the previous turning point being a trough. A minimum duration requirement is not necessary for the deviation cycle since the parameter specification of the CF-filter implies a minimum duration between two subsequent peaks or troughs of 3 years. Since subcycles with a duration less than 3 years are filtered out, the conditions on the dating algorithm turn out not to be binding as no local peaks (or troughs) materialize in the sense that $(1-L)\,LI_{t-1} > 0$ and $(1-L)\,LI_t < 0$ while $LI_t < 0$.

The dating of the turning points of the coincident indicators is graphically shown in Figure 1. The turning point dates of GDP, the reference-index and the eleven selected leading indicator variables are shown in Table 3. The dating of the turning points of the leading indicators occurred after alignment of the leading indicator with the number of months as shown in the last row under the heading lead time. Three observations result from the Table 3. The most important observation is that the nineties show two subcycles, which are visible in almost all selected leading indicators and industrial production, but not in GDP. Secondly, almost all indicators miss turning points and/or show false signals. A missed turning point is a turning point in the reference index, which the leading indicator fails to signal. A false signal occurs when the leading indicator shows a turning point, which eventually does not materialize in the reference index. Thirdly, the lead times of the leading indicator, as determined by the maximum cross correlation $\rho^{\max}$, show a lot of variation amongst the different turning points, but are not systematically biased and hence need no additional adjustment.

The leading indicator variables are primarily selected on meeting the statistical criteria of a minimum lead of 7 months and a minimum cross-correlation of 0.7. As Table 2 shows, a couple of variables that did pass the statistical tests are nevertheless not selected because the signal they represent is already accounted for by other leading indicator variables that are closely related. The composite leading business cycle index consists of the unweighted average of eleven leading indicators after standardisation. Figure **??** shows the composite coincident and leading indices based on data available in Februari 2009 . The x-axis of Figure **??** corresponds to the trend level and so, a positive (negative) output gap means that the level of economic activity lies above (below) its trend level. Moreover,

Figure 2: Composite coincident and leading indices



an upward (downward) sloping output gap means that the level of economic activity is growing quicker (slower) than its trend growth.

The eleven selected leading indicator variables make up a balanced representation consisting of three financial series, four business and consumer survey results and four real activity variables, of which two supply and two demand related. The three financial variables are the short term interest rate, the yield curve and the stock price index. Low short term interest rates reduces financing costs and will spur investment demand. The AEX stock price index consists of the 25 most actively traded shares in the Netherlands and indicates the expected future corporate profitability and the underlying growth potential. Since the AEX index is dominated by multi-national companies, the leading properties of this variable also reflect external economic developments. Moreover, Jansen en Nahuis (2003) show that negative returns on the stock exchange lower consumer wealth and consumer confidence, thereby causing a reduction in consumer spending. The term structure of the interest rate encompasses two transmission mechanisms: the expected future short term interest rates and the term premium for higher risk and/or lower liquidity. Berk (1998) provides a literature review of the information content of the term structure of interest rates. An inverse curve is usually observed at the start of a recession period and acts therefore as a predictor, see for instance Estrella en Mishkin (1998). The four business and consumer survey results are expected business activity, the IFO-indicator of future expectations, domestic consumer confidence and the OECD´s leading indicator for the Unites States. The IFO-indicator represents the economic expectations of producers in the Netherlands´ largest trading partner Germany.

The OECD´s leading indicator for the U.S. reflects the short term outlook of the world´s largest economy, whose business cycle is shown to be leading for the G7 countries, (see for instance Osborn *et al.*, 2005). Finally, two supply related real activity variables are the order arrivals and the stock of finished products and the two consumption related real activity variables are the real house price and the registrations of new cars. Housing wealth, and therefore real house price changes, are an important factor in the total wealth of consumers. The registrations of new cars is a variable that quickly reacts to alterations in the business cycle.

Table 4 presents the compositions of the business cycle indicators for the Netherlands of different institutions. As a robustness check, Table 4 shows that almost all selected indicator variables in this study are also used by the institutions mentioned, even though different concepts of the business cycle and different trend estimators are applied. The only two unique leading indicator variables for the Netherlands are the real house price and the registration of new cars, although this latter variable is used in the OECD´s leading indicators for other countries. Using the real house price as a leading indicator is however also unique in an international context. The main source of difference with respect to the indices presented in Table 4 refers to the coincident index, which is more broadly based than just on industrial production, more timely available than GDP releases and excludes business cycle measurement based on sentiment indicators.

Table 4: Composition of business cycle indicators for the Netherlands by different institutions

	CPB	DNB	OECD	Rabobank	CBS*
Since	1990	1985	around 1980	1982	2005
Latest revision	2003	2006	2002	2006	2005
Versions	the Netherlands, short index in 10 components and a long index	the Netherlands, U.S., Japan and the largest European countries	OECD-countries	the Netherlands	the Netherlands
Reference Series	gross domestic product (interpolated)	industrial production	industrial production	industrial production	
				volume retail trade	
				exptected business activity processing industry	
				IFO current index	
Leading indicators	bankruptcies	3-months AIBOR/EURIBOR	Stock market index (AEX)	10-years interest rate	producer confidence
	producer confidence (retailers)	term structure of interest rates (yield curve)	IFO-indicator for Germany	3-months AIBOR/EURIBOR	unemployed labour force
	issued building permits (business, residential)	IFO-indicator for Germany	stock finished products	growth credit supply of the Rabobank organisation	consumer confidence
	OECD-indicator (Europe, United States)	expected business activity	level order position	order arrival processing industry	jobs of employees
	real money aggregate (M3)	real money aggregate (M1)	expected order arrivals	IFO-indicator of future expectations in Germany	temporary jobs
	consumer-confidence (willingness to buy, economic climate)		expected production		consumer survey; purchases of durables
	order arrivals (foreign, domestic, industry)				exports
	10-years interest rate				fixed capital formation
	business activity (expected, realized, construction, occupancy rate industry)				business survey: orders received
	IFO-indicator				gdp
	Evaluation stocks				total household consumption
					industrial production
					vacancies
					10-years bond yield
					bankruptcies
Horizon	3-4 months	7 months	±6 maanden	5 months	
Trend filter	CF	CF	PAT (/HP)	CF	HP

Notes:

* CBS does not publish forecasts

5 Indicator revision analysis

Since a policy institution uses the business cycle indicator as an instrument to measure and forecast the business cycle, the real-time assessment of the cyclical motion is a key focus. The cyclical indicator in the period t, say $CI_{t|t}$ is based on information available up to and including period t. If new data at period $t+1$ becomes available, the cycle for period t based on all data $CI_{t|t+1}$can change, since the real-time allocation of the dynamics to structural and cyclical forces is necessarily uncertain as information on the future path of the economy is missing. Orphanides en Van Norden (2002) conclude that the unreliability of the cyclical estimator, that is the difference between the mid-sample $CI_{t|t}$ and the end-of-sample $CI_{t|T}$ estimates, is quite high for a broad class of detrending methods. Schleicher (2004) shows that the CF-filter is the optimal end-of-sample band-pass filter if the underlying time series follows a random walk (cf Van Norden, 2002). For the last available observation, the CF-filter is effectively a one-sided filter, which becomes increasingly two-sided as more and more data becomes available. Since the filter weights are highest for the leads and lags close to the target date, adding new data substantially contributes to the estimate of the cycle. This feature is even more prominent if the underlying series is seasonally unadjusted since then the variability of the newly arriving data transforms directly into volatile tail-behavior. The CF-filter is designed to filter out trending behavior at the cost of induced higher volatility at the business cycle frequencies and relatively pronounced leakage of the higher, that is seasonal, frequencies. So, the vulnerability of the CF-filter for high frequency movements translates into volatile tail behavior, although the filtered cycle will converge ever closer to its true value.

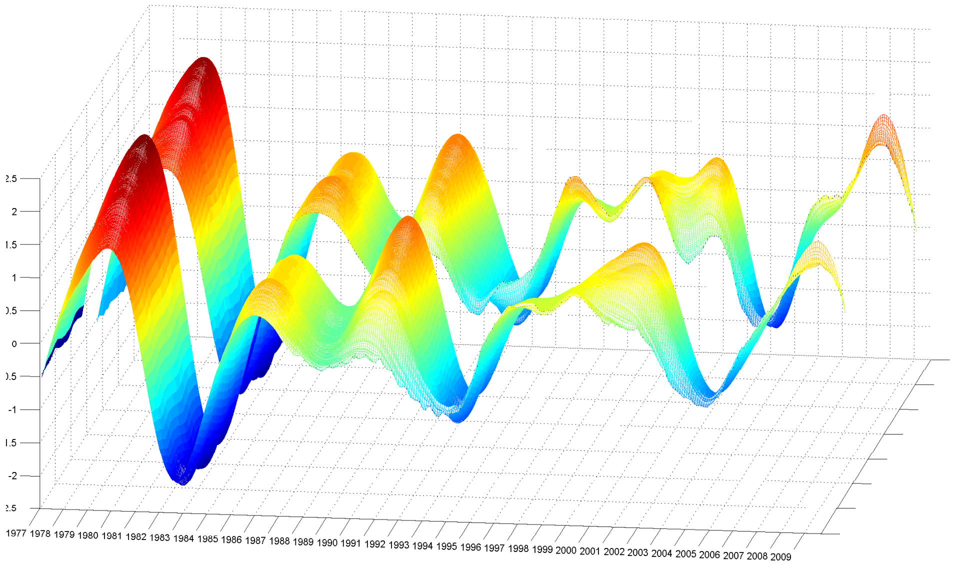
The filtered cycle at the target date is reasonably converged if it is based on the maximum length of a complete cycle, say k, of which half are future observations of the underlying variable. The filter window at the target date then covers at least a complete cycle symmetrically[9]. In order to stabilize the volatile behavior of the tail, we average as much as possible over half a cycle. More precisely, let $CI^{CF}_{t-i|t-i+j}$ be the CF-filtered value of the cycle for period $(t-i)$ given data until period $(t-i+j)$, then the estimated cycle $CI_{t-i|t}$ for the period $t-i$ given data until and including period t is the average of the $(i+1)$ available CF-filtered values : $CI_{t-i|t} = \frac{1}{i+1}\sum_{j=0}^{i} CI^{CF}_{t-i|t-i+j} \;\; \forall\, i = 0, ..., k$.

In order to assess the reliability of the coincident and leading indices, we calculated their sequential updates starting with the indicator that runs from February 1977 until January 1988 and ending with the one that runs from Februay 1977 until February 2009. The graph in the front of Figure 3 represents the collection of sequential updates for the coincident indicator and the graph in the back for the leading indicator. The z-dimension of the graph reveals the maturing of both indicators as for each point in time the end-of-sample estimates converge to their mid-sample equivalents.

Figure 3 shows that the standard deviation of the end-of-sample estimates is lower than its mid-sample equivalent. As more data arrives, the peaks and troughs of both indicators become increasingly more pronounced. In order to

[9]Note that Baxter en King (1999) recommend a symmetric window size of $\frac{1}{2}k = 12$ periods in case an upperbound of 32 periods for quarterly data is imposed and a size of $\frac{1}{2}k = 3$ periods for an upperbound of 8 periods for yearly data.

Figure 3: Consecutive updates of the coincident and leading indices



quantify the size of the adjustments, we calculate for the coincident indicator CI and the leading indicator LI the mean difference, $\text{mean}\left(Y_{t|t+i-1} - Y_{t|t+66}\right)$, $Y = \{CI, LI\}$ and the mean absolute difference, $\text{mean}\left|Y_{t|t+i-1} - Y_{t|t+66}\right|$, between the mid-sample estimate of the cycle for which 66 months of future observations are available, $Y_{t|t+66}$, and the corresponding estimates based on a smaller number of i available observations, $Y_{t|t+i-1}$, $i = 1, 12, 23, 34, 45, 56$ where $i = 1$ is the end-of-sample estimate, over the sample period $t = 1988.2 - 1999.11$.All estimates from February 1988 onwards are at least based on a full cycle of past observations. Moreover, the estimates for November 1999 can be calculated including up to half the duration of a cycle of future observations. Finally the results, which are presented in Table 5, are averages over one complete cycle.

The mean absolute size of the adjustment between the end-of-sample and mid-sample estimates of the coincident indicator, which is a standardized variable, is 0.32. The mean absolute size of the adjustment of the leading indicator is of the same order of magnitude. The larger cross-section of eleven variables of the composite leading indicator, as compared to the three variables that constitute the composite coincident indicator, does not diminish the magnitude of the adjustment. The cyclical estimates of the individual variables get adjusted in the same direction and consequently do not cancel out in the cross-sectional average. The mean size of the adjustment errors of the coincident and leading indicators are also of the same order of magnitude, albeit of different signs. The negative mean adjustment error of the coincident indicator entails that the upward adjustments around the peak was on average bigger than the downward adjustments around the trough in the sample period. On average both indicators converge towards each other, which implies that the mid-sample correlation is higher than end-of-sample one. The difference between both indicators $\left(CI_{t|t+i-1} - LI_{t|t+i-1+7}\right)$ at each point in time t evolves as a larger number of observations i becomes available. Note that the end-of-sample estimate of the coincident index ($i = 1$) corresponds for every period with the estimate of the leading index for which the lead of 7 additional observations are available. Table 5 shows that the mean absolute difference between both indicators declines and stabilizes after 24 additional observations.

Table 5: The size of adjustment of the indicators from their mid-sample estimates.

variable/observations	i=1	i=12	i=23	i=34	i=45	i=56
CI, absolute	0.32	0.28	0.20	0.12	0.06	0.03
LI, absolute	0.35	0.27	0.18	0.12	0.08	0.05
CI-LI, absolute	0.23	0.20	0.18	0.17	0.17	0.17
CI	-0.12	-0.10	-0.06	-0.03	-0.01	-0.00
LI	0.12	0.08	0.04	0.03	0.02	0.01
CI-LI	-0.16	-0.10	-0.04	0.01	0.04	0.05

Notes:

Mean of the size of the adjustment of the coincident and leading indicators from their mid-sample estimates as more observations become available. The sample period is t=1988.2-1999.11

6 Indicator based GDP forecasting

Marcellino (2006, Chapter 4) reviews the literature and practices on the choice and evaluation of leading indicator models, possibly combined into composite indexes, and the development of more sophisticated methods to relate the indicators to a forecast for a target variable. The objective is to compare the forecasts of quarterly growth rates for GDP growth based on monthly indicator variables with the ones based on the composite indices. Rnstler *et al.* (2009) performs a large-scale GDP forecasting exercise involving large data sets for ten European countries and the euro area and conclude that factor models exploiting large monthly data sets outperforms traditional bridge equations. However, the Dutch results of Rnstler *et al.*'s (2009) analysis, which are based on the 14 single indicator variables that comprise the composite indices, perform remarkably well.

We replicate the exercise based on the quarterly Vector Autoregressive Model (VAR) that consists of a bivariate VAR containing GDP growth and the quarterly aggregate of a monthly indicator with the number of lags less than 5 quarters and determined by the Schwartz Information Criterion. The resulting forecast is then the unweighted average of the bivariate VARs containing each of the monthly indicator variables. The forecasting performance is confronted with the results of a pure autoregressive process for GDP growth, AR(1) and the naive forecast consisting of the recursive mean. The indicator based forecasts consist of: i) All, VAR forecasts based on all the fourteen single indicator variables[10]; ii) All synch, idem but after synchronisation of the indicator variables with the corresponding leads reported in Table 2; iii) Ci, bivariate VAR based on the composite coincident index $CI_{t|T}$ for $t = 1, ..., T$ and $T = 2009.2$; iv) Li, bivariate VAR based on the composite leading index $CI_{t|T}$; v) Cirt, bivariate VAR based on the pseudo real-time composite coincident index $CI_{t|t}$; vi) Lirt, bivariate VAR based on the pseudo real-time composite leading index $LI_{t|t}$. The exercise starts with the estimation period of 1978.2-1999.4 and evaluation period 2000.1-2008.4 for a forecast horizon $h = -1, 0, 1, 2$. The forecast horizon $h = -1$ represents the "forecast" for the preceding quarter for which no GDP data release is yet available. Assume that the objective is to forecast GDP growth in the second quarter. We start forecasting in January: this forecast refers to next quarter GDP, $h = 1$, or first month one quarter ahead forecast. In moving forward in time we produce a forecast in each month, and with the GDP flash estimate being published in mid-August, run the final forecast on 1 August. We denote the latter as the second month preceding quarter "forecast", which is actually a backcast. This sequence of forecasts is applied to each quarter of our out-of-sample period.

Table 6 presents the forecast performance as the Root Mean Squared Error (RMSE) times 100 for different model specifications. The results suggest that the gains from synchronisation as represented by the difference in performance between the All and All synch specifications seem to be limited. Moreover, the composite leading index doesn't improve very substantially over the coincident index. However, the gains from the trend-cycle decomposition as represented by the difference between Ci and Li over All and All synch are quite substantial even when considering the pseudo real-time equivalents. Finally, Table 6 shows

[10] So, this specification is identical to the Dutch one in Rnstler *et al.* (2009) apart from the sample and forecast period.

a 25% improvement of the forecast performance of the LI over the autoregressive AR(1) specification.

Table 6: Forecasting performance of the leading indicators.

h	AR(1)	Naive	All	All synch	Ci	Li	Cirt	Lirt
2	150.01	156.64	146.17	142.17	84.35	83.19	120.01	121.81
1	139.90	155.70	127.62	125.53	78.25	78.15	105.02	101.63
0	123.51	154.59	104.05	102.91	71.63	71.13	86.49	81.83
-1	90.50	153.28	84.32	84.09	65.34	64.25	72.83	69.70

Notes:

The forecast perfomance is presented as RMSE*100 for different model specifications over the sample period 2000.1-2008.4. The model specifications consist of the naive and an autoregressive process for GDP growth. The other specifications consists of averages of bivariate VARs including the fourteen single indicator variables or one of the composite indices, which can be synchronised and/or in pseudo real-time format.

7 Conclusion

Policy institutions employ a business cycle indicator as an instrument to measure and forecast the business cycle and its turning points. This study constructs a business cycle indicator for the Dutch economy along the lines of the NBER-approach that consists of a reference index, which represents the current stage of the business cycle, and the indicator, which represents the developments of the cycle in the near future. The business cycle indicator is a deviation cycle that can be interpreted as an output gap, which is the fluctuation of economic activity around some trend. Hence, a most crucial choice regarding the deviation cycle is the method to extract the cyclical and trend component out of a time series of observations of an economic variable. In this study, we apply Christiano en Fitzgerald's (2003) approximate band-pass filter, which isolates from a time series all the intrinsic cyclical motion consisting of waves with lengths longer than 3 years and shorter than 11 years lengths. The minimum duration requirement of 3 years aims to filter out minor cycles and seasonal cycles such that the resulting business cycle matches more closely its benchmark of cyclical GDP.

The composite reference index is based on several coincident indicators that measure real economic activity being industrial production, household consumption and staffing employment. For an indicator to be useful in practice, a timely update and therefore a limited publication delay for new observations of the source data is a crucial condition to be met. Since economic fluctuations originate from different sources, we combine a number of relevant leading indicators into a single composite index. The main selection criterion for the leading indicators are the lead time and the statistical conformity with the business cycle as represented by the composite reference index. The eleven selected leading indicator variables together make up a balanced representation of near future cyclical developments. The composite leading indicator consists of three financial series, four business and consumer survey results and four real activity variables, of which two supply and two demand related.

We analyse the revision of the cyclical estimator, that is the extent to which cyclical estimates are adjusted over time as more data becomes available. This feature emerges since the real-time assessment of the current cyclical position is dependent on the future, and therefore unknown, path of the economy. We show that the composite reference index and the composite leading index converge towards each other on average as more data becomes available. Consequently, the in-sample fit between both indicators is better than the end-of-sample fit. Finally, we compare the forecasts for quarterly growth rates of GDP based on the observed monthly indicator variables with the ones based on the composite indices. The results show that the composite indices perform better than their underlying indicator variables separately. Moreover, the gain in performance results from the trend-cycle decomposition.

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A Appendix:

A.1 Data description

This paragraph describes the data underlying the reference index and the leading indicator respectively.

A.1.1 Coincident indicators

As described in section 3.1, the composite reference index of the revised DNB-business cycle indicator consists of three monthly variables, that is industrial production, the household consumption and the staffing employment. The industrial production series is readily available with a long history. The time series of consumer expenditures and the staffing employment need to be constructed as described below.

Consumer expenditures The basic series for consumer expenditures consist of the household consumption, which is published each month with a delay of 7 to 8 weeks and dates back to 1995. The variable is the volume index of household consumption, that is consumptive expenditures by households and non-profit institutions operating on behalf of households. The consumption by households only contains those parts of the actual individual consumption for which households pay themselves, which makes the variable more sensitive to business cycles. Moreover, consumption concerns the domestic consumption on Dutch territory and includes the consumption of foreigners. The series is available on a monthly basis since 1995. The series is extended over the period 1977-1995 with linearly interpolated quarterly data of private consumption from the National Accounts.

Staffing employment The basic series for the staffing employment consists of the number of staffing hours employed through staffing agencies in the Netherlands. The number of staffing hours relate to staffing service agencies belonging to SBI[11] code 74501, whose main activity is the matching of staffing employees of phase A. These employees are paid by the staffing agency, work on a contractual basis and have no regular labour contract. The basic series of staffing employment is published each quarter with a delay of 5 months and dates back to 1999.

In order to construct the history of staffing services and to overcome the publication delay, we make use of the staffing services turnover data from Randstad Netherlands. The number of staffing employees employed through Randstad Netherlands has been recorded from 1960 onwards. Randstad Netherlands occupies since decades a stable market share of around 40%. The available data cover the period 1967q1 until 2003q4 containing the number of persons of staffing employment employed through Randstad Netherlands as published in De Groot en Franses (2005). Moreover, a third series is available from 2005 onwards describing the market turnover as published by the Dutch association of

[11] The Dutch statistics office CBS employs a systematic hierarchical classification system for economic activities called the *Standaard Bedrijfsindeling* (SBI) that is compatible with the International Standard Industrial Classification of All Economic Activities (ISIC).

temporary works agencies[12] (ABU), which represents 60% of the market. The data is published with a delay of only a couple of weeks and is sampled in 13 administrational periods of 4 weeks a year. The transformation for each year of 13 periods to 12 months runs with the following algorithm: month(i)=(14-i)/13*period(i)+i/13*period(i+1) for i=1,...,12.

So, the first part of the final series covers the period 1967-1999 and consists of the number staffing employees employed through Randstad. The second part consists of the total number of staffing hours employed in the Netherlands as published by the CBS and deals with the period 1999 until the most recently covered quarter. The third part consists of the monthly turnover data from the ABU and are connected additively after indexation with the overlapping year as the base.

[12] see http://www.abu.nl